Swami Ramanand Teerth Marathwada University, Nanded

Latur Raod, Vishnupuri, Nanded - 431606 (Maharashtra) India

(Established in 1994, Recognized By the UGC U/s 2(f) and 12(B), NAAC Re-accredited with 'B++' Grade, a State University)

Synopsis

Title:

"EFFECT OF DHYANA (MEDITATION) ON COGNITIVE LOAD"

Submitted to the University in partial fulfilment of registration to

Ph.D. Programme

In the subject

Electronics and Telecommunication Engineering

under the Faculty of

Science & Technology

Submitted by

Vrashali Eknathrao Hotalkar

Under the supervision of

Dr. R.R. MANTHALKAR

Professor, Department of Electronics and Telecommunication Engineering.

Research Centre

Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded (M.S.) India.2022-2023

CONTENTS

CONTENTS 2
Introduction 4
Literature Survey 6
Challenges 8
Problem Definition 9
Future Research Plan 9
Conclusion 10
References: 11

Abstract

Dhyana, a fundamental aspect of meditation originating from ancient Eastern practices, has garnered significant attention in contemporary research for its potential effects on cognitive processes. This synopsis delves into the exploration of how the practice of dhyana influences cognitive load, shedding light on its implications for mental well-being and cognitive performance. Research suggests that regular practice of dhyana can modulate cognitive processes and reduce cognitive load in various ways. Dhyana promotes attentional control and enhances the ability to sustain focused attention, thereby reducing distractions and cognitive interference. In many scientific domains, the electroencephalogram (EEG) is an invaluable tool for both clinical and research applications. On the other hand, standard gadgets typically cost several thousand dollars. In addition to taking time to prepare, using the device can be a little painful. It would be advantageous if more recent consumer electronics, which are cheaper and easier to use, could also be utilized for research. We used a consumer EEG device in our experiment to capture the Buddhist monks' brainwaves while they engaged in various activities, such as meditation. After that, we examined the recordings to show that a low-cost gadget has sufficient capabilities and may be applied to research.

Introduction

Cognitive load refers to the amount of mental effort required to perform a task or process information. It comprises three main components: intrinsic load (the inherent complexity of the task), extraneous load (additional cognitive burden imposed by task conditions), and germane load (mental effort devoted to learning and understanding).

Research suggests that regular practice of dhyana can modulate cognitive processes and reduce cognitive load in various ways. Dhyana promotes attentional control and enhances the ability to sustain focused attention, thereby reducing distractions and cognitive interference. By fostering a state of mental clarity and relaxation, dhyana may mitigate stress-related cognitive load, leading to improved cognitive functioning and decision-making. The cultivation of mindfulness through dhyana encourages metacognitive awareness, allowing individuals to regulate cognitive processes more effectively and optimize cognitive resources.

a.ElectroEncephaloGram B)Structure of Electrode

Dhyana practices such as focused attention meditation and loving-kindness meditation have been associated with changes in brain structure and function, potentially influencing cognitive load and cognitive performance.

Understanding the relationship between dhyana and cognitive load has implications for various domains, including education, healthcare, and workplace settings.

Incorporating dhyana practices into cognitive training programs or interventions may enhance learning, memory, and problem-solving abilities while reducing cognitive fatigue and burnout. Dhyana-based interventions have shown promise in alleviating symptoms of anxiety, depression, and other mental health conditions by regulating cognitive processes and emotional reactivity.

Further research is needed to elucidate the specific mechanisms underlying the effects of dhyana on cognitive load and to explore its long-term impact on cognitive functioning and well-being.

C) Electrode Placement System

Cognitive load refers to the amount of mental effort required to perform a task or process information.

It comprises three main components: intrinsic load (the inherent complexity of the task), extraneous load (additional cognitive burden imposed by task conditions), and germane load (mental effort devoted to learning and understanding).

Research suggests that regular practice of dhyana can modulate cognitive processes and reduce cognitive load in various ways.

Dhyana promotes attentional control and enhances the ability to sustain focused attention, thereby reducing distractions and cognitive interference.

By fostering a state of mental clarity and relaxation, dhyana may mitigate stress-related cognitive load, leading to improved cognitive functioning and decision-making.

The cultivation of mindfulness through dhyana encourages metacognitive awareness, allowing individuals to regulate cognitive processes more effectively and optimize cognitive resources.

Dhyana practices such as focused attention meditation and loving-kindness meditation have been associated with changes in brain structure and function, potentially influencing cognitive load and cognitive performance.

Understanding the relationship between dhyana and cognitive load has implications for various domains, including education, healthcare, and workplace settings.

Incorporating dhyana practices into cognitive training programs or interventions may enhance learning, memory, and problem-solving abilities while reducing cognitive fatigue and burnout.

Dhyana-based interventions have shown promise in alleviating symptoms of anxiety, depression, and other mental health conditions by regulating cognitive processes and emotional reactivity.

Further research is needed to elucidate the specific mechanisms underlying the effects of dhyana on cognitive load and to explore its long-term impact on cognitive functioning and well-being.

Literature Survey

1. **Cognitive Load During Multitasking Can Be Accurately Assessed Based on Single Channel Electroencephalography Using Graph Methods (GUOHUN ZHU 1,2, (Member, IEEE), FANGRONG ZONG 3, HUA ZHANG1, BIZHONG WEI2, AND FENG LIU 1, (Member, IEEE))-** Mental workload has been widely estimated based on electroencephalography (EEG) in the frequency domain. However, simple frequency features are not entirely accurate indicators of the cognitive load because surface EEG signals are weak, nonstationary and randomness. We hypothesize that graph methods, which analyse the relationship between each point and other points of the EEG signals, may provide a more precise identi_cation of the mental load.

2. **Cognitive Workload Recognition Using EEG Signals and Machine Learning: A Review Yueying Zhou , Shuo Huang , Ziming Xu , Pengpai Wang , Xia Wu , *Member, IEEE,* and Daoqiang Zhang , *Member, IEEE* -** The concept of mental or cognitive burden is receiving more and more attention. It is commonly understood to be the ratio of an individual's available resource resources were required beyond the task. In practical settings, having too much or too little work will have an adverse effect. that of the operator. that of the operator. As a result, understanding cognitive workload becomes crucial.As of right now, cognitive workload assessments can be separated into measurements that are objective and subjective. Subjective workload assessment techniques and the National Aeronautics and Space Administration-task load index are two surveys that are used to quantify cognitive workload. Subjective assessments are based on the felt feeling and selfrating of operators.

3. **Cross-Domain MLP and CNN Transfer Learning for Biological Signal Processing: EEG and EMG -JORDAN J. BIRD 1, JHONATAN KOBYLARZ 2, DIEGO R. FARIA 1, ANIKÓ EKÁRT 1, AND EDUARDO P. RIBEIRO-**For the first time, the question of whether cross-domain transfer learning can affect models' classification performance after training on electroencephalographic (brainwave) as well as data on electromyography (muscular waves). The best models of each are used to transfer initial weights, and learning proceeds from this initial point of departure. We contend, in contrast to the traditional random weight distribution initialization method, that knowledge can be effectively transferred from EMG to EEG and vice versa. Additionally, we contrast the outcomes with a model refined by ImageNet weights to identify the transfer of meaningful domain-specific information as opposed to generic picture rules that can be acquired from a variety of sources and domains.

4. **The Effects of 8-Week Mindfulness-Based Stress Reduction Program on Cognitive Control: an EEG Study -".** In this paper author Taken together, the behavioral and electrophysiological results suggest that the mindfulness practice enhanced the ability to implement both proactive and reactive cognitive control processes.

5. **6.An Evaluation of the EEG Alpha-to-Theta and Theta-to-Alpha Band Ratios as Indexes of Mental Workload Bujar Raufi* and Luca Longo-** Numerous studies show that the alpha and theta bands of the EEG have the potential to be useful indicators of cognitive strain. There isn't much evidence, though, to support this assertion. This research attempts to evaluate and examine the effects of the alpha-to-theta and theta-to-alpha band ratios on facilitating the

development of models able to distinguish between self-reported mental workload perceptions. Using a collection of raw EEG data, 48 participants completed a multitasking SIMKAP test as an induced task demanding exercise in addition to a resting activity. Using frontal and parietal electrode clusters, band ratios were calculated. High-level independent features from the frequency and temporal domains that were taken from the computed ratios across time were used to build and test the model.

6. **Analysis of the Meditation Brainwave from Consumer EEG Device *Decho Surangsrirat and Apichart Intarapanich*** - In the publication, a brief overview of my experience analyzing brain activity using a consumer EEG equipment. The consistency results appear to indicate that there may be a chance to employ a consumer gadget for research purposes. Even though they are preliminary, the studies are encouraging and may spur more research in this area. To find out more about the relationships and validate the results, we plan to conduct additional trials in the future with a sizable cohort of seasoned meditation practitioners in addition to the control group. Additional techniques, such wavelet transform, could potentially be used to assist in signal analysis. Furthermore, a startling side effect of meditation could be found in addition to stress reduction and improved emotional state.

7. **EEG-based discrimination of different cognitive workload levels from mental arithmetic Zheng Yang Chin, Xin Zhang, Chuanchu Wang, Kai Keng Ang**- The amount of mental effort needed to complete a cognitive activity, or cognitive strain, can be measured by tracking changes in neurophysiological quantitative methods like electroencephalograms (EEG). This work examines how well an EEG-based Brain-Computer Interface (BCI) can distinguish between various degrees of mental arithmetic difficulty. Ten participants' EEG data was recorded as they completed mental addition at three different difficulty levels: easy, medium, and hard. Following the extraction of EEG characteristics utilizing band power and Common Spatial Pattern features, features were chosen using Fisher Ratio in order to train a linear discriminant classifier. The average accuracy for two classes (easy versus hard tasks) and three classes (mental arithmetic) was 90% and 66%, respectively, according to the results of 10-fold cross-validation.

8. **Cognitive Load During Multitasking Can Be Accurately Assessed Based on Single Channel Electroencephalography Using Graph Methods GUOHUN ZHU 1,2, (Member, IEEE), FANGRONG ZONG 3, HUA ZHANG1, BIZHONG WEI2, AND FENG LIU 1, (Member, IEEE) -** This article applies three graph features to distinguish cognitive load tests according to subject perceptions and task differences. There are greater clustering coefficient characteristics. in contrast to those of the remainder states, during the period.
There is a significant difference (p-value < 0.0001) between the F8, P8, T8, and AF4 channels in the right hemisphere with high cognitive load and those of low cognitive load. For the first time, graph-based mental EEG research demonstrates that the temporal and frontal areas are both responsive to high Cognitive Load During Multitasking Can Be Accurately Assessed Based on Single-Channel EEG cognitive load. The earlier research, on the other hand, merely discovered distributions. The suggested methodology is useful for determining tiredness and maximizing learning.

Challenges

1.Cognitive Affective Mindfulness Scale-Revised.

2. Intra-Subject Classification Performance

3. Classical Machine Learning Methods For Cognitive Workload Recognition

Problem Definition

This research is aimed towards development of novel Cognitive behavior using dhyana classification.

In our research work the following problem(s) can be addressed:

- Design a Model to distinguish behavior of youth pre and post dhyana.
- Evaluating the proposed model's accuracy.
- Identifying significant features of dhyana using cognitive load

Future Research Plan

2.

Year wise plan of work & targets	
Years	**Work plan**
First Year	Literature review, coursework, determining the advantages and disadvantages of the cognitive behavior classification, defining the problem, establishing objectives, and performing a feasibility study.
Second Year	Basic implementation, Development of Detection model and formulate results.
Third Year	Paper writing and publishing

Conclusion

Analyzing the EEG recordings likely involved processing the raw data to extract relevant features and patterns associated with different mental states. This could include techniques such as spectral analysis, event-related potential (ERP) analysis, or machine learning algorithms to classify brainwave patterns. Overall, leveraging consumer EEG devices for research purposes opens up new possibilities for studying brain function and mental states in diverse populations and settings. It democratizes access to neuroscience research and allows for a broader exploration of the human mind.

References:

1) Busra T. Susam , Kelly Beck, Safaa Eldeeb, Caitlin M. Hudac, Philip A. Gable, Caitlin Conner, Murat Akcakaya , Nathan T. Riek , Susan White, and Carla Mazefsky , " **Quantitative EEG Changes in Youth With ASD Following Brief Mindfulness Meditation Exercise**" . IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 30, 2022.

2) Dino Dvorak, Andrea Shang, Samah Abdel-Baki, Wendy Suzuki, and André A. Fenton," **Cognitive Behavior Classification from Scalp EEG Signals**" IEEE transactions on neural systems and rehabilitation engineering, vol. 26, no. 4, April 2018.

3) Seyedeh Arefeh Rezazadeh Yazd , Sahar Gashtil , Mahboobeh Moradpoor , Sedigheh Pishdar , Pantea Nabian , Zahra Kazemi , Mahdi Naeim ," **Reducing depression and anxiety symptoms in patients with Parkinson's disease: The effectiveness of group cognitive behavioral therapy" ,** Science direct research article , Parkinsonism & Related Disorders22 May 2023.

4) Zachary D. Cohen, Nora M. Barnes-Horowitz, Courtney N. Forbes, Michelle G. Craske, **"Measuring the active elements of cognitive-behavioral therapies",** Science direct research article 2023.

5) Elizabeth A. Hoge , Naomi M. Simon , Kristin Szuhany , Benjamin Feldman , David Rosenfield , Susanne Hoeppner , Emma Jennings , Sat Bir Khalsa , Stefan G. Hofmann , **"Comparing Kundalini Yoga, cognitive behavioral therapy, and stress education for generalized anxiety disorder: Anxiety and depression symptom outcomes",** Science direct research article September 2023.

Ms. Vrashali E.Hotalkar
(Research Scholar)

Dr. R.R Manthalkar
(Supervisor)